Machine Learning for Radiometer Calibration

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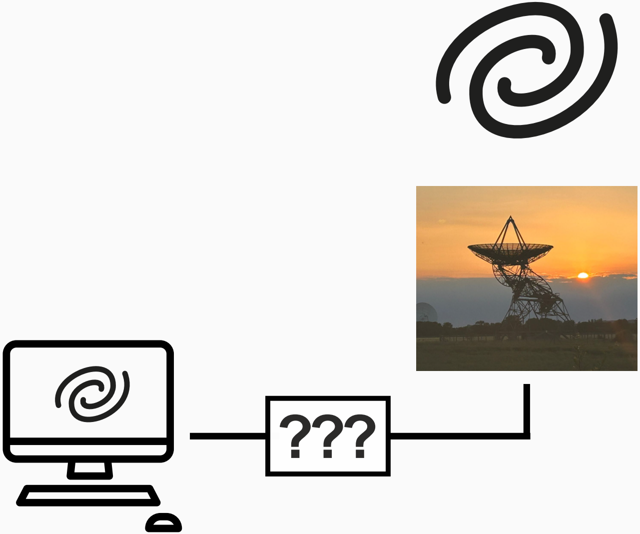
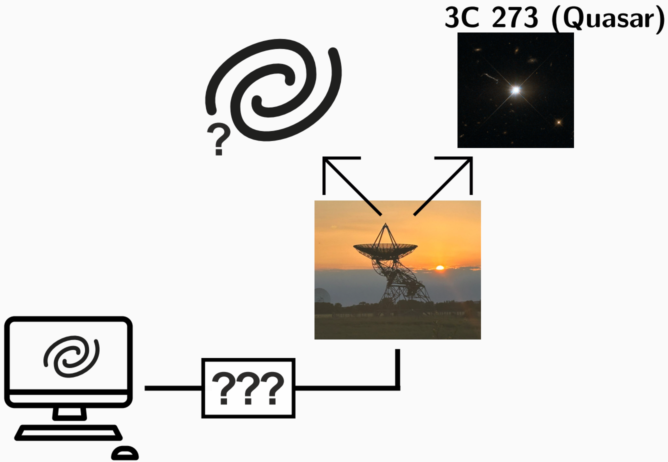
Radiometer calibration overview

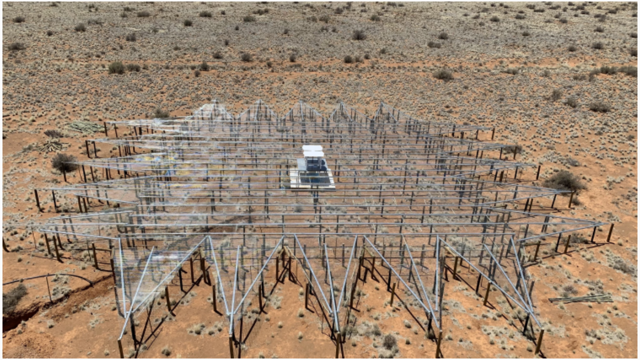
What is calibration?



How to calibrate?



Why is calibration in Global 21cm Cosmology difficult?



We measure *sky averaged* signal.

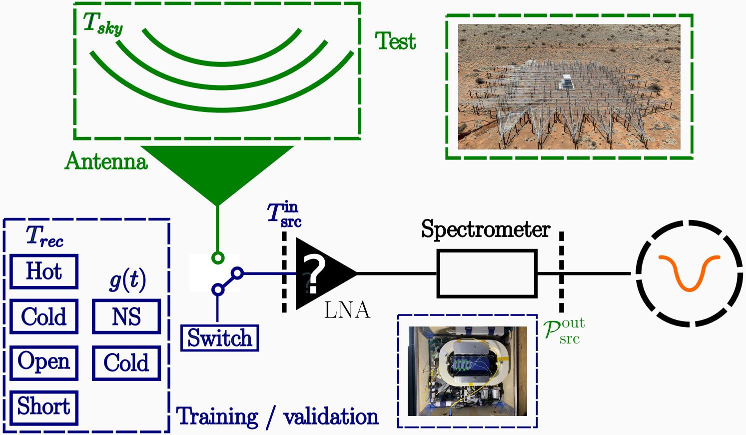
Antenna LNA impedance mismatch

Very faint signal.

The physical system

Process:

- Switch between sources to generate training data.
- Calibration sources with known temperature train neural net.
- Predict T_{src} of antenna.



How to calibrate (in a bit more detail...)?

Objective: Map input temperature to output power.

Key Factors:

- LNA introduces time-dependent gain, $g(t)$.
- Impedance mismatch adds noise (T_{rec}) to the system.

Link Output Power to Input Temperature:

$$P_{\text{out}}^{\text{src}} = gM \times (T_{\text{in}}^{\text{src}} + T_{\text{rec}}) \qquad (1)$$

$$M = (1 - |\Gamma_{\text{cal}}|^2) \left| \frac{\sqrt{1-|\Gamma_{\text{rec}}|^2}}{1-\Gamma_{\text{cal}}\Gamma_{\text{rec}}} \right|^2$$

Note: All parameters above are frequency-dependent, but the notation has been simplified here and thereafter for convenience.

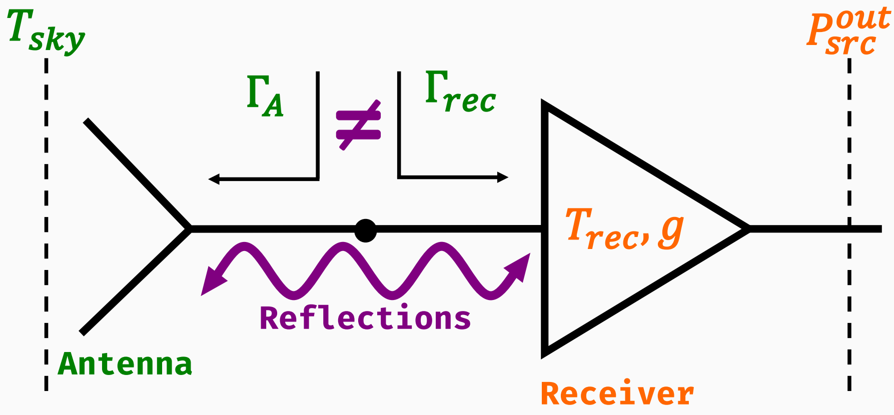


Figure 1: Schematic of the receiver system showing the signal path from antenna to digitizer

Dealing with reflections...

$$P^{\mathrm{src}}_{\mathrm{out}} = gM\left(T^{\mathrm{src}}_{\mathrm{in}} + T_{\mathrm{rec}}\right) \tag{2}$$

Noise Parameter Equation:

$$P^{\mathrm{src}}_{\mathrm{out}} = gM\left(T^{\mathrm{src}}_{\mathrm{in}} + T_{\mathrm{min}} + T_0\frac{4R_N}{Z_0}\frac{|\Gamma_{\mathrm{src}} - \Gamma_{\mathrm{opt}}|^2}{(1-|\Gamma_{\mathrm{src}}|^2)(1+|\Gamma_{\mathrm{opt}}|^2)}\right) \tag{3}$$

- g - Gain
- T_{min} - Minimum Noise Temperature
- R_N - Noise Resistance
- Γ_{opt} - Optimum Reflection Coefficient

Noise Wave Equation:

$$\begin{aligned} P^{\mathrm{src}}_{\mathrm{out}} = g\Bigg[& T_0 + T_{\mathrm{unc}}|\Gamma_{\mathrm{s}}|^2\left|\frac{\sqrt{1-|\Gamma_{\mathrm{rec}}|^2}}{1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}}\right|^2 \\ & + T_{\mathrm{s}}(1-|\Gamma_{\mathrm{s}}|^2)\left|\frac{\sqrt{1-|\Gamma_{\mathrm{rec}}|^2}}{1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}}\right|^2 + T_{\mathrm{cos}}\Re\left(\Gamma_{\mathrm{s}}\frac{\sqrt{1-|\Gamma_{\mathrm{rec}}|^2}}{1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}}\right) \\ & + T_{\mathrm{sin}}\Im\left(\Gamma_{\mathrm{s}}\frac{\sqrt{1-|\Gamma_{\mathrm{rec}}|^2}}{1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}}\right)\Bigg] \end{aligned} \tag{4}$$

- Γ_{s} - Source Reflection Coefficient
- Γ_{rec} - Receiver Reflection Coefficient
- T_{s} - Source Temperature
- $P^{\mathrm{src}}_{\mathrm{out}}$ - Power out
- $T_{\mathrm{unc,\ cos,\ sin}}$ - Noise wave parameters
- T_0 reference temperature

Calibration Equation

Typically, substitute in the noise wave parameter equation here (gains cancel)

$$T^*_{\mathrm{cal}} = T_{\mathrm{NS}} \frac{P_{\mathrm{cal}} - P_L}{P_{\mathrm{NS}} - P_L} + T_L \tag{4}$$

Make some matching assumptions and re arrange:

$$\begin{aligned} T_{\mathrm{s}} = {} & T_{\mathrm{NS}} \left(\frac{P_{\mathrm{s}} - P_{\mathrm{L}}}{P_{\mathrm{NS}} - P_{\mathrm{L}}} \right) \frac{|1 - \Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}|^2}{1 - |\Gamma_{\mathrm{s}}|^2} + T_{\mathrm{L}} \frac{|1 - \Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}|^2}{1 - |\Gamma_{\mathrm{s}}|^2} - T_{\mathrm{unc}} \frac{|\Gamma_{\mathrm{s}}|^2}{1 - |\Gamma_{\mathrm{s}}|^2} + \\ & - T_{\mathrm{cos}} \frac{\Re\left(\frac{\Gamma_{\mathrm{s}}}{1 - \Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}}\right) |1 - \Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}|^2}{(1 - |\Gamma_{\mathrm{s}}|^2)\sqrt{1 - |\Gamma_{\mathrm{rec}}|^2}} - T_{\mathrm{sin}} \frac{\Im\left(\frac{\Gamma_{\mathrm{s}}}{1 - \Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}}\right) |1 - \Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}|^2}{(1 - |\Gamma_{\mathrm{s}}|^2)\sqrt{1 - |\Gamma_{\mathrm{rec}}|^2}} \end{aligned} \tag{5}$$

Note: We end up with 5 parameters that need to be estimated to calibrate the system.

Calculating the error

By partial derivatives To find the error in T_s, we propagate the errors in Γ_s, Γ_{rec}, P_L, P_{NS}, and P_s:

$$(\Delta T_s)^2 = \left(\frac{\partial T_s}{\partial \Gamma_s}\Delta\Gamma_s\right)^2 + \left(\frac{\partial T_s}{\partial \Gamma_{rec}}\Delta\Gamma_{rec}\right)^2 + \left(\frac{\partial T_s}{\partial P_L}\Delta P_L\right)^2 + \left(\frac{\partial T_s}{\partial P_{NS}}\Delta P_{NS}\right)^2 + \left(\frac{\partial T_s}{\partial P_s}\Delta P_s\right)^2. \quad (5)$$

Calculating the error

$$(\Delta T_s)^2 = \left(\frac{\partial T_s}{\partial \Gamma_s}\Delta\Gamma_s\right)^2 + \left(\frac{\partial T_s}{\partial \Gamma_{rec}}\Delta\Gamma_{rec}\right)^2 + \left(\frac{\partial T_s}{\partial P_L}\Delta P_L\right)^2 + \left(\frac{\partial T_s}{\partial P_{NS}}\Delta P_{NS}\right)^2 + \left(\frac{\partial T_s}{\partial P_s}\Delta P_s\right)^2. \tag{6}$$

$$\frac{\partial T_s}{\partial P_L} = T_{\mathrm{NS}}\frac{|1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}|^2}{1-|\Gamma_{\mathrm{s}}|^2}\cdot\frac{P_{\mathrm{s}}-P_{\mathrm{NS}}}{(P_{\mathrm{NS}}-P_{\mathrm{L}})^2}, \tag{7}$$

$$\frac{\partial T_s}{\partial P_{NS}} = -T_{\mathrm{NS}}\frac{|1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}|^2}{1-|\Gamma_{\mathrm{s}}|^2}\cdot\frac{P_{\mathrm{s}}-P_{\mathrm{L}}}{(P_{\mathrm{NS}}-P_{\mathrm{L}})^2}, \tag{8}$$

$$\frac{\partial T_s}{\partial P_s} = T_{\mathrm{NS}}\left(\frac{1}{P_{\mathrm{NS}}-P_{\mathrm{L}}}\right)\frac{|1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}|^2}{1-|\Gamma_{\mathrm{s}}|^2}. \tag{9}$$

$$\frac{\partial T_s}{\partial \Gamma_{rec}} = \frac{\partial A}{\partial \Gamma_{rec}} + \frac{\partial B}{\partial \Gamma_{rec}} + \frac{\partial D}{\partial \Gamma_{rec}} + \frac{\partial E}{\partial \Gamma_{rec}}. \tag{10}$$

$$\frac{\partial T_s}{\partial \Gamma_s} = \frac{\partial A}{\partial \Gamma_s} + \frac{\partial B}{\partial \Gamma_s} + \frac{\partial C}{\partial \Gamma_s} + \frac{\partial D}{\partial \Gamma_s} + \frac{\partial E}{\partial \Gamma_s}. \tag{11}$$

$$A = T_{\mathrm{NS}}\left(\frac{P_{\mathrm{s}}-P_{\mathrm{L}}}{P_{\mathrm{NS}}-P_{\mathrm{L}}}\right)\frac{|1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}|^2}{1-|\Gamma_{\mathrm{s}}|^2}, \tag{12}$$

$$B = T_{\mathrm{L}}\frac{|1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}|^2}{1-|\Gamma_{\mathrm{s}}|^2}, \tag{13}$$

$$C = -T_{\mathrm{unc}}\frac{|\Gamma_{\mathrm{s}}|^2}{1-|\Gamma_{\mathrm{s}}|^2}, \tag{14}$$

$$D = -T_{\cos}\frac{\Re\left(\frac{\Gamma_{\mathrm{s}}}{1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}}\right)|1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}|^2}{(1-|\Gamma_{\mathrm{s}}|^2)\sqrt{1-|\Gamma_{\mathrm{rec}}|^2}}, \tag{15}$$

$$E = -T_{\sin}\frac{\Im\left(\frac{\Gamma_{\mathrm{s}}}{1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}}\right)|1-\Gamma_{\mathrm{s}}\Gamma_{\mathrm{rec}}|^2}{(1-|\Gamma_{\mathrm{s}}|^2)\sqrt{1-|\Gamma_{\mathrm{rec}}|^2}}. \tag{16}$$

Calculating the error

Using $T_{\mathbf{NS}}\frac{P_{\mathbf{cal}}-P_L}{P_{\mathbf{NS}}-P_L}+T_L$

$$(\Delta T_s)^2=\left(\frac{\partial T_s}{\partial P_s}\Delta P_s\right)^2+\left(\frac{\partial T_s}{\partial P_L}\Delta P_L\right)^2+\left(\frac{\partial T_s}{\partial P_{NS}}\Delta P_{NS}\right)^2 \tag{17}$$

$$+\left(\frac{\partial T_s}{\partial \Gamma_s}\Delta \Gamma_s\right)^2+\left(\frac{\partial T_s}{\partial \Gamma_{rec}}\Delta \Gamma_{rec}\right)^2. \tag{18}$$

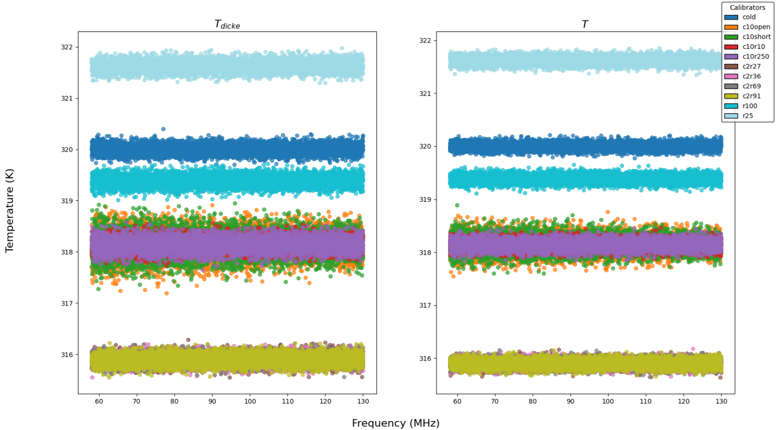
Using noise wave parameters only

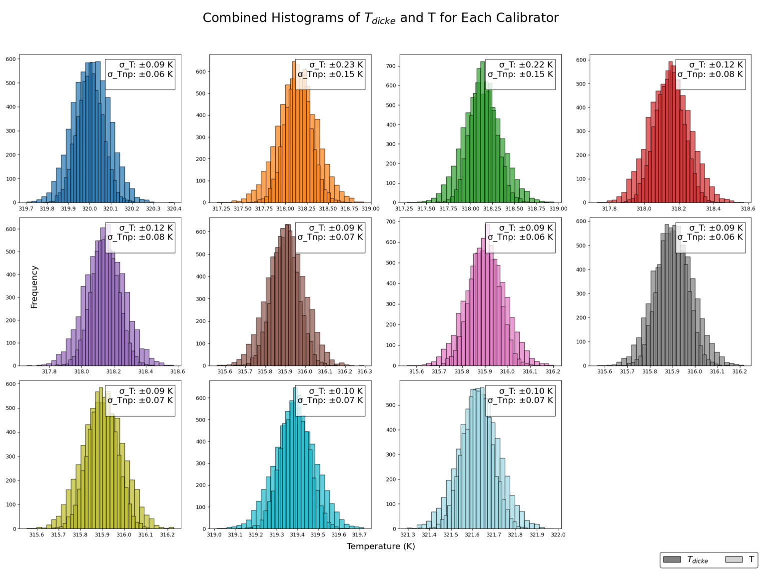
$$(\Delta T_{\mathrm{s}})^2=\left(\frac{\partial T_{\mathrm{s}}}{\partial P_{\mathrm{s}}}\Delta P_{\mathrm{s}}\right)^2 \tag{19}$$

$$+\left(\frac{\partial T_{\mathrm{s}}}{\partial \Gamma_{\mathrm{s}}}\Delta \Gamma_{\mathrm{s}}\right)^2+\left(\frac{\partial T_{\mathrm{s}}}{\partial \Gamma_{\mathrm{rec}}}\Delta \Gamma_{\mathrm{rec}}\right)^2. \tag{20}$$

Note that this argument applies for both noise parameters and noise wave parameters.

There is more noise when using $T_{\mathrm{NS}} \frac{P_{\mathrm{cal}} - P_L}{P_{\mathrm{NS}} - P_L} + T_L$





Noise amplified by **30%** when using

$$T_{\mathrm{NS}}\frac{P_{\mathrm{cal}}-P_L}{P_{\mathrm{NS}}-P_L}+T_L$$

Why not fit noise (wave) parameters directly?

Noise Parameter Equation:

$$P_{out}^{src} = gM\left(T_{in}^{src} + T_{min} + T_0\frac{4R_N}{Z_0}\frac{|\Gamma_{src} - \Gamma_{opt}|^2}{(1-|\Gamma_{src}|^2)(1+|\Gamma_{opt}|^2)}\right) \tag{21}$$

Noise Wave Equation:

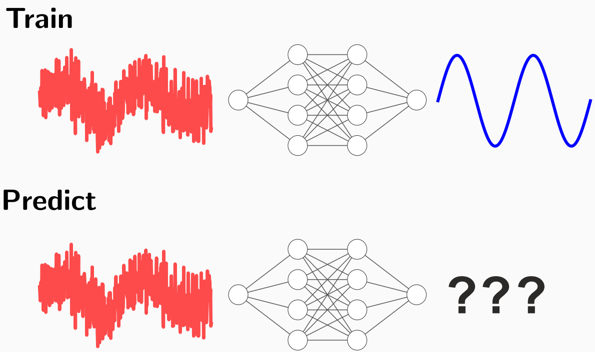
$$\begin{aligned} P_{out}^{src} = g\Bigg[& T_0 + T_{unc}|\Gamma_s|^2\left|\frac{\sqrt{1-|\Gamma_{rec}|^2}}{1-\Gamma_s\Gamma_{rec}}\right|^2 \\ & + T_s(1-|\Gamma_s|^2)\left|\frac{\sqrt{1-|\Gamma_{rec}|^2}}{1-\Gamma_s\Gamma_{rec}}\right|^2 + T_{cos}\Re\left(\Gamma_s\frac{\sqrt{1-|\Gamma_{rec}|^2}}{1-\Gamma_s\Gamma_{rec}}\right) \\ & + T_{sin}\Im\left(\Gamma_s\frac{\sqrt{1-|\Gamma_{rec}|^2}}{1-\Gamma_s\Gamma_{rec}}\right)\Bigg] \end{aligned} \tag{22}$$

We still end up with 5 unknowns, as before.

Radiometer calibration with machine learning

How/why?

- Can predict noise wave parameters using machine learning.
- Could apply method to noise parameters.
- Predict **directly** on noise parameters on frequency by frequency basis.
- Maleable to environmental changes.



How to calibrate with machine learning

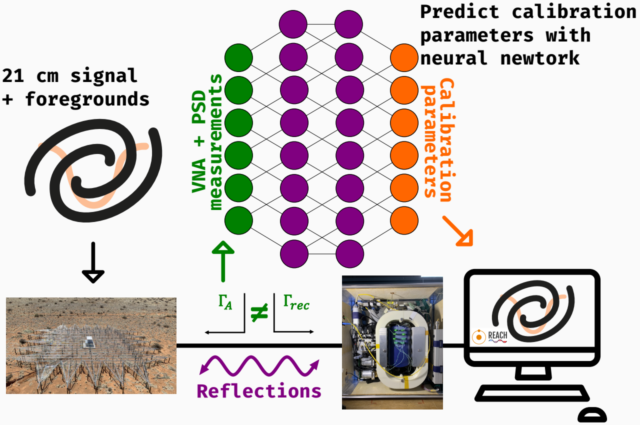


Figure 2: High-level overview of the machine learning-based calibration framework

Machine learning calibration steps

1. Define the Loss Function

Regress over measured power and predicted power.

$$\mathcal{L} = \frac{1}{n} \sum_{i=1}^{n} \left(\mathcal{P}_{\text{measured},i} - \mathcal{P}_{\text{pred},i}\right)^2 \tag{23}$$

2. Write Down the Equation for $\mathcal{P}_{\text{pred}}$

Using the noise wave formalism, relate $\mathcal{P}_{\text{pred}}$ to T_{src}.

$$\begin{aligned}\mathcal{P}_{\text{pred}} &= g \cdot M \Bigg(T_{\text{in}}^{\text{src}} \\ &\quad + T_{\text{min}} + T_0 \frac{4R_N}{Z_0} \frac{|\Gamma_{\text{src}} - \Gamma_{\text{opt}}|^2}{(1 - |\Gamma_{\text{src}}|^2)(1 + |\Gamma_{\text{opt}}|^2)} \Bigg)\end{aligned} \tag{24}$$

3. Minimise the Loss Function

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}) \tag{25}$$

parameter vector $\boldsymbol{\theta}$ includes all tunable parameters in the model:

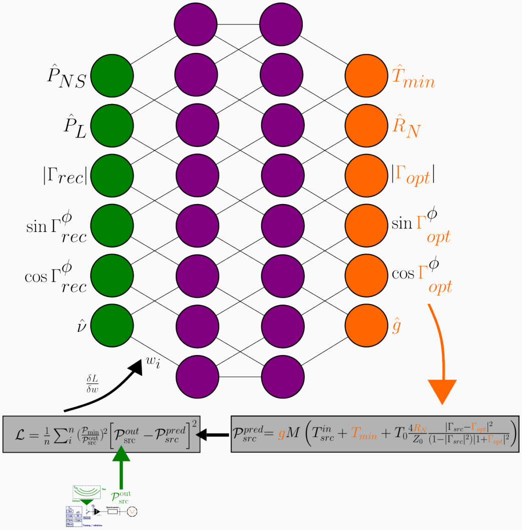
$$\boldsymbol{\theta} = \{g, T_{\text{min}}, R_N, \Gamma_{\text{opt}}^{\phi}, |\Gamma_{\text{opt}}|) \tag{26}$$

4. Rearrange and Predict (T_{src}) using $\boldsymbol{\theta}^*$

$$\begin{aligned}T_{\text{src}} &= \frac{\mathcal{P}_{\text{pred}}}{g^* \cdot M} \\ &\quad - \left(T_{\text{min}}^* + T_0 \frac{4R_N^*}{Z_0} \frac{|\Gamma_{\text{src}} - \Gamma_{\text{opt}}^*|^2}{(1 - |\Gamma_{\text{src}}|^2)(1 + |\Gamma_{\text{opt}}^*|^2)} \right)\end{aligned} \tag{27}$$

Structure:

- Input thermistor and VNA measurments.
- Also input frequency.
- Predict noise parameters.
- Regress over loss function.



Testing on internal validation source

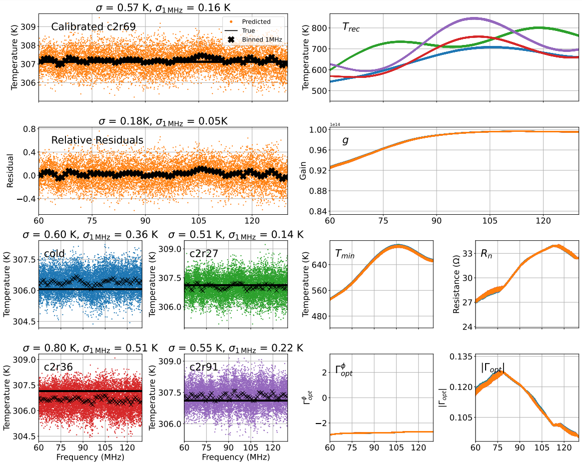


Figure 3: Temperature calibration using internal sources on the REACH receiver

End to end 21cm experiment simulation

End to end simulation

We have shown we can calibrate an internal source, we now test the method on as part of the broader system (simulated).

1) Simulate full receiver chain

↓

2) Simulate realistic antenna with 21cm signal

↓

3) Fit noise parameters to simulated receiver chain

↓

4) Calibrate 'simulated' antenna

↓

5) Fit 21cm signal using REACH pipeline

Predicted vs True Antenna Temperature

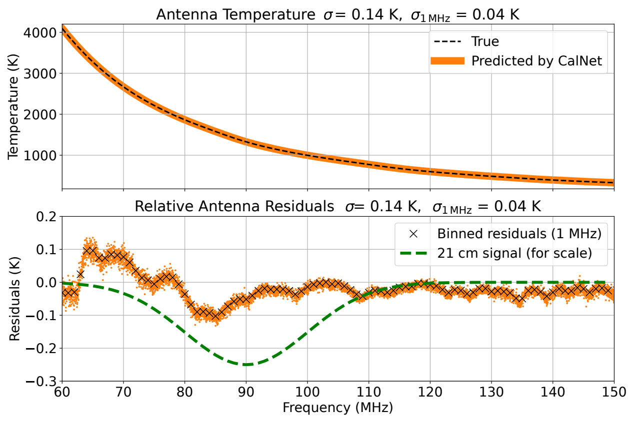


Figure 4: The top panel shows the predicted antenna temperature in orange, with the true temperature overlaid in black dashes

Inferred 21cm Signal

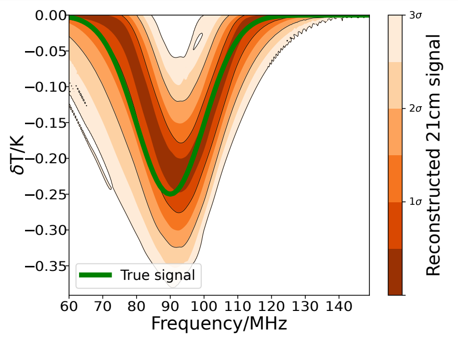


Figure 5: Left: Reconstructed 21cm signal with posterior (orange) and true signal (green)

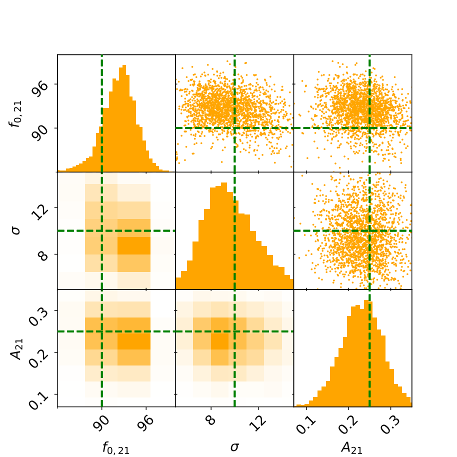
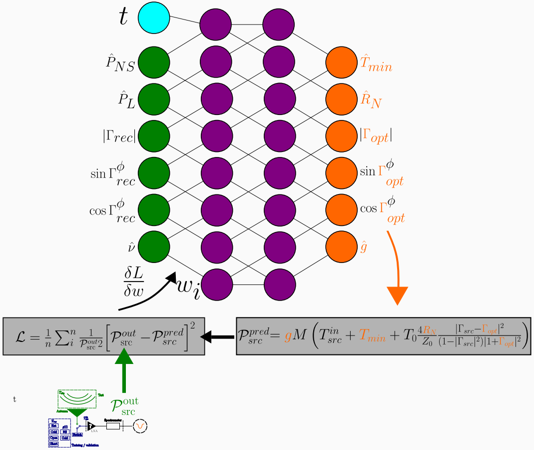


Figure 6: Right: Posterior plots of recovered 21cm signal parameters

Learning non-linear time-dependent system drift

Neural Network Time Evolution



Simulation pipeline for radiometer calibration

calibration-simulation Private

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About

Calibration observation simulation codes for REACH

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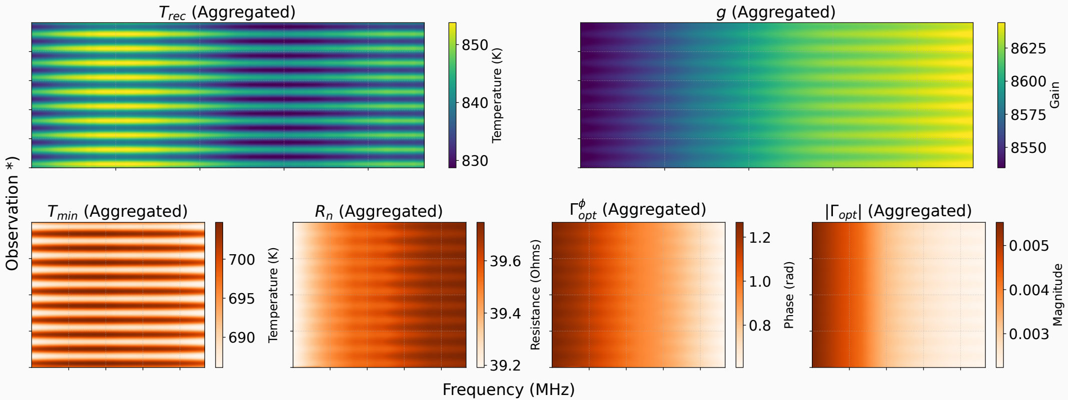
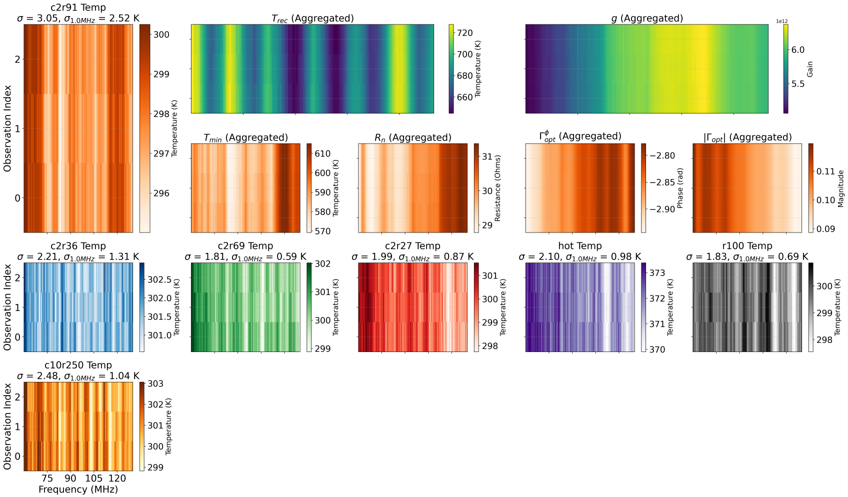
Inject system drift

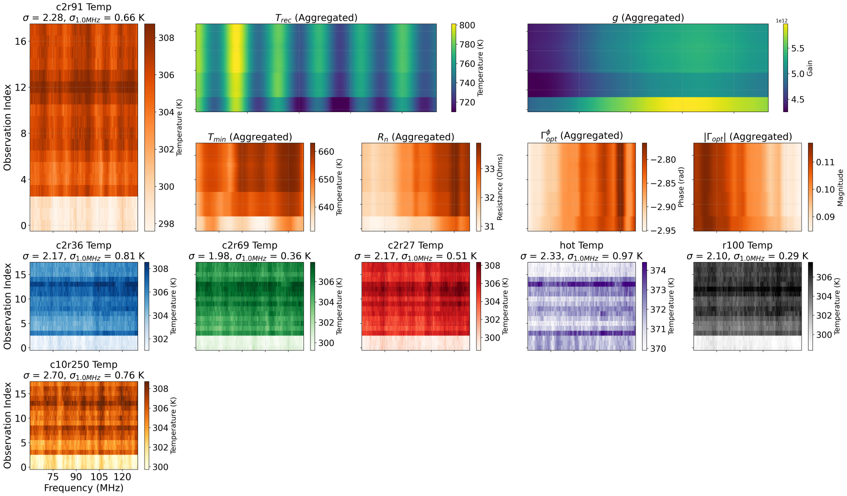


Inject a time varying sinusoid into $T_{\min}$ and predict the noise parameters $\rightarrow$ the network recovers this 'system drift'

Single night, many observations



Many nights, many observations



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[Submitted on 23 Apr 2025]

Radiometer Calibration using Machine Learning

S. A. K. Leeney, H. T. J. Bevins, E. de Lera Acedo, W. J. Handley, C. Kirkham, R. S. Patel, J. Zhu, D. Molnar, J. Cumner, D. Anstey, K. Artuc, G. Bernardi, M. Bucher, S. Carey, J. Cavillot, R. Chiello, W. Croukamp, D. I. L. de Villiers, J. A. Ely, A. Fialkov, T. Gessey-Jones, G. Kulkarni, A. Magro, P. D. Meerburg, S. Mittal, J. H. N. Pattison, S. Pegwal, C. M. Pieterse, J. R. Pritchard, E. Puchwein, N. Razavi-Ghods, I. L. V. Roque, A. Saxena, K. H. Scheutwinkel, P. Scott, E. Shen, P. H. Sims, M. Spinelli

Radiometers are crucial instruments in radio astronomy, forming the primary component of nearly all radio telescopes. They measure the intensity of electromagnetic radiation, converting this radiation into electrical signals. A radiometer's primary components are an antenna and a Low Noise Amplifier (LNA), which is the core of the ``receiver'' chain. Instrumental effects introduced by the receiver are typically corrected or removed during calibration. However, impedance mismatches between the antenna and receiver can introduce unwanted signal reflections and distortions. Traditional calibration methods, such as Dicke switching, alternate the receiver input between the antenna and a well-characterised reference source to mitigate errors by comparison. Recent advances in Machine Learning (ML) offer promising alternatives. Neural networks, which are trained using known signal sources, provide a powerful means to model and calibrate complex systems where traditional analytical approaches struggle. These methods are especially relevant for detecting the faint sky-averaged 21-cm signal from atomic hydrogen at high redshifts. This is one of the main challenges in observational Cosmology today. Here, for the first time, we introduce and test a machine learning-based calibration framework capable of achieving the precision required for radiometric experiments aiming to detect the 21-cm line.

Comments: Under peer review for publication in Nature Scientific Reports as part of the Radio Astronomy collection
Subjects: **Instrumentation and Methods for Astrophysics (astro-ph.IM)**; Cosmology and Nongalactic Astrophysics (astro-ph.CO); Artificial Intelligence (cs.AI)
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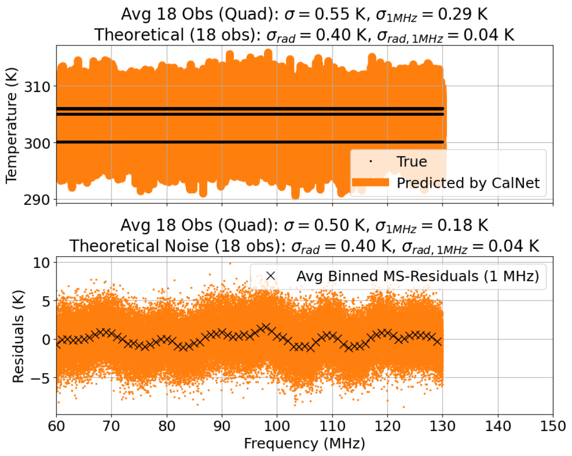
From: Samuel Alan Kossoff Leeney [view email]
[v1] Wed, 23 Apr 2025 15:10:25 UTC (25,900 KB)

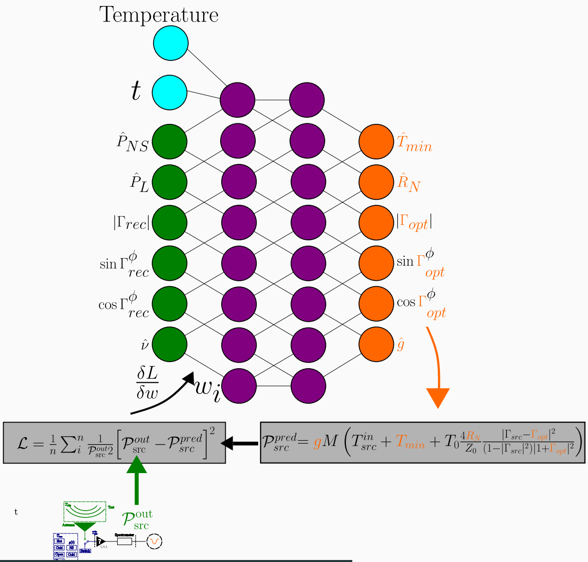
Calibration Performance



- Significant improvement when combining many nights
- Calibration down to 0.18K
- Getting close to theoretical noise

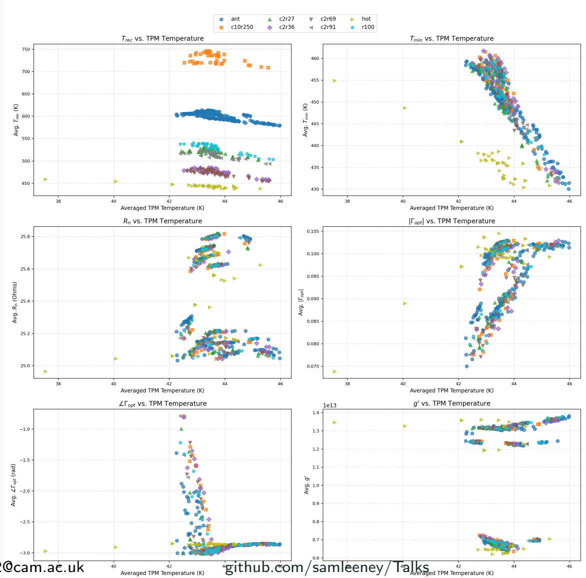
Modeling system drift from other complex system effects

Modeling environmental features



We can train on features that cannot be modeled analytically

Fitting environmental features against fitted noise parameters



Correlate noise parameters with environmental data

Thank you!

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